Center for Environmentally Sustainable Transportation in Cold Climates

The Impact of Snowfall on Airport Operations and Delays.

Jukwan Lee and Jia Yan
School of Economic Sciences
Washington State University

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Prepared by: Jia Yan

Center for Environmentally Sustainable Transportation in Cold Climates
University of Alaska Fairbanks
P.O. Box 755900
Fairbanks, AK 99775

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Flight delays or cancelations due to snowfall are a costly inconvenience, not only to airports but also to airlines, passengers and society as a whole. However, no quantitative research has ever been done to provide an analytical explanation about the issue. Though being a reliable alternative to melt snow on the runway and mitigate flight delays, the Heated Pavement System is not adopted in any US airports because of concerns over the initial investments and maintenance costs being higher than the economic loss from delays during unpredictable snowfall days. Combining weather and domestic flight data in Boston and Los Angeles regions, we analyze the benefits and costs associated with installing the Heated Pavement System. Using two advanced econometric methods, the Difference in Difference in Difference (DDD) and the nearest neighbor matching, we first develop a Delay Analysis model to evaluate the exact effect of snowfall on flight delays, and then we calculate the delay costs. Based on the empirical findings, we conduct cost-benefit analysis of installing HPS at the three airports in Boston area. Our results indicate that HPS is feasible for airports with a great number of flights and passengers, such as Boston Logan airport.

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By

Jukwan Lee and Jia Yan

School of Economic Sciences

Washington State University

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EXECUTIVE SUMMARY

Flight delays or cancelations due to snowfall are a costly inconvenience, not only to airports but also to airlines, passengers and society as a whole (Ball et al., 2010). However, no quantitative research has been done to provide an analytical explanation about the issue. As a result, policymakers do not have a clear picture of the choices available. Though being a mature technology and a reliable alternative to melt snow and mitigate flight delay, the heated pavement system (HPS) has not been adopted at any US airports because of concerns over the initial investments and maintenance costs being higher than the economic loss from delays during unpredictable snowfall days.

This study analyzes the benefits and costs of installing an HPS on an airport runway. To quantify the benefits, we first estimated the impact of snowfall on flight delays. To implement the delay analysis model, we constructed a unique data set by merging the flight on-time performance data with the weather information. We collected each operator's on-time performance raw data in the US Bureau of Transportation Statistics and rebuilt our dataset by individual airport. We established the airport weather data by matching the closest weather station record from National Oceanic Atmospheric Administration (NOAA) to the airport and matched it with the closest departure and arrival time of each flight. We then applied the Differencein-Difference in Difference (DDD) method and the matching analysis to accurately identify the impact on airport delays of runway snow and other relevant factors. The treatment group we selected includes four airports in the Great Boston area where there are regular snowstorms during the winter. The control group selected includes four airports in the Greater Los Angeles area where it never snows. Based on the empirical findings, we conducted cost-benefit analysis of installing HPS at the three airports

in Boston area. The results indicate that HPS is feasible for airports with a large number of flights and passengers, such as Boston Logan airport.

Keywords: Airport delays, Runway Snow Accumulation, Heated Pavement System, Costs and Benefits Analysis, Installation Costs, Airport Operation Costs, Econometric Analysis

CHAPTER 1.0 Introduction

Flight delays or cancelations due to snowfall are a costly inconvenience, not only to airports but also to airlines, passengers and society as a whole (Ball et al., 2010). However, no quantitative research has been done to provide an analytical explanation about the issue. As a result, policymakers do not have a clear picture of the choices available. Most transport category aircraft are prohibited from operating on runways covered with untreated ice or more than 1/2 inch of snow or slush. Currently, mechanical (plow, brushes, and blowers) and chemical systems (deicing and anti-icing agents) are standard methods to mitigate the effect of snowfall. However, when it comes to handling extra heavy and consecutive snow, both systems are far from effective. Heated pavement system (HPS) is a rising and reliable alternative to melt any snowfall on the runway instantly.

Although a mature technology, no airport in the US uses HPS. The initial investments and maintenance costs of HPS are thought to be significantly higher than the unforeseen economic loss from possible flight delays and cancellations from some bad snowy days. Based on weather and domestic flight data, this study analyzed the benefits and costs associated with installing the HPS and aims to find out the feasibility of the HPS. Using two advanced econometric methods, the Difference in Difference in Difference (DDD) and the Nearest Neighbor Matching, it developed a Delay Analysis model to evaluate the exact effect of snowfall on flight delays, then calculated the delay costs. Previous research determined the costs of the HPS installation and maintenance.

To implement the delay analysis model, we constructed a unique data set by merging the flight on-time performance data with the weather information. The flight data are from the US

Bureau of Transportation Statistics between April 2014 and March 2015, a period during which several severe winter storms happened. We recorded data for 824,869 actual domestic flights from eight US airports, three from the Greater Boston metropolitan and five from the Greater Los Angeles Area. We constructed the airport weather data by matching the closest weather station record from National Oceanic Atmospheric Administration (NOAA) to the airport and matched it with the closest departure and arrival time of each flight.

This study contributes to aviation delay literature in two aspects. First, we focused on fat tails of catastrophic weather events that happen occasionally and are difficult to predict. Previous empirical approaches usually proposed a prediction model without these exogenous events, while this study includes this weather variable in the prediction model to produce a more accurate estimation for the delay effect. Secondly, we suggest comprehensive benefit and cost analysis on both the supply and demand sides. New snow removal infrastructure investment not only solves the delay problem but also triggers the equilibrium change from increased airport capacity, passenger demand and airfare. We try to suggest a new assessment framework incorporating welfare change in this shift in demand and supply curve. Practically, this result answers the commercial applicability of the new HPS.

Chapter 2 presents related researches on flight delay and investments in airport infrastructure. In Chapter 3.0, we present some background about snow removal system and heated pavement runway installation. After describing the research design in Chapter 4.0 and data in Chapter5.0, we estimate the delay model in Chapter 6.0.

CHAPTER 2.0 Related Literatures

A flight delay occurs if an airline flight takes off or lands later than its scheduled time. The Federal Aviation Administration (FAA) considers a flight delayed when it is 15 minutes later than its scheduled time. Since June 2003, airlines with more than 0.5% of the regular domestic passenger revenue share in the US have reported on-time data and delays. Cause for delays include air carriers, extreme weather, national aviation systems, late aircrafts and security.

Flight delays result in significant costs to the airlines, passengers, and society as a whole. The direct costs of delays include additional fuel consumption, additional crew and capital. Flight delays can also lead to longer passenger travel times, environmental externalities and spillover macroeconomic effects (Kafle & Zou, 2016). The annual cost of domestic flight delays in the United States ranges from $14 billion (ATA, 2009) to $41 billion (Joint Economic Commission, 2008). The estimated cost per minute ranges from $61 (ATA, 2009) to $80 (FAA, 2013). Table 1 shows the estimated delay costs of previous studies. Such high costs drive practical analysis and prediction of the delays and development of better management systems in the aerospace industry. With such high costs, it is necessary for aviation industry to have practical analysis to better predict flight delays.

Table 1 Cost Of Airport Delay

Delay cost type	Source	Cost estimates
Total delay cost, annual	Joint Economic Committee (2008)	$41 billion
	Air Transport Association (2009)	$14 billion
	FAA/Nextor (2017)	$26.6 billion
	Ball et al. (2010)	$32.9 billion
Cost per minute of delay	Airlines for America (2017)	$68.48
	FAA Foam 41 Data (2013)	$79.72

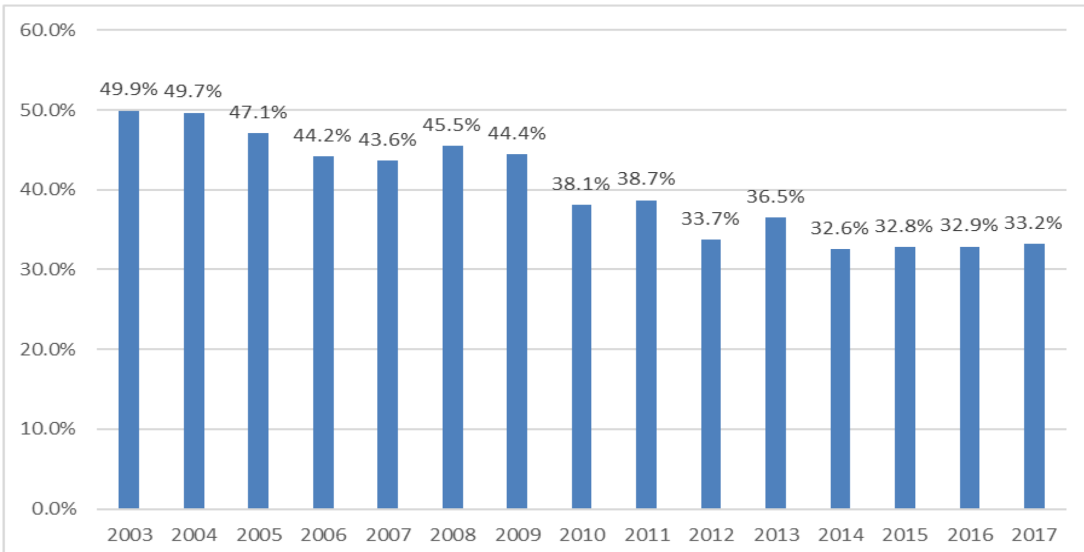
Delay cost type	Source	Cost estimates
	Cook, Tanner, & Anderson (2004)	€72
	Air Transportation Association (2009)	$ 60.99
	Cook & Tanner (2011)	€81

Note: Air Transport Association (ATA) changes their name to Airlines for America (A4A)

Delays also cause an indirect price by adversely affecting airline scheduling and aircraft utilization, and creating additional labor expenses (Britto et al, 2012). Using a multi logic model to estimate passenger costs, Morrison and Winston (1989) found that a 1% increase in on-time performance creates a value of $1.21 per round trip per customer. Britto et al‘s research indicates that US consumers would gain about $1.5-2.5 per passenger from a 10% reduction in delays. Total passenger delay cost is estimated up to 16.7 billion dollars. The lost in air transportation demand adds an additional $3.9 billion to the cost side (Britto et al., 2012).

Other studies have examined the total cost of delays. According to the report prepared for the Senate Joint Economic Committee, the total cost to airlines, passengers, and the rest of the economy is estimated to be as high as $41 billion in 2007, including $31 billion in direct costs and $10 billion in spillovers costs (JEC 2008). The Air Transport Association, using a different methodology, estimates a total cost of $14 billion for year 2008, excluding spillovers (ATA, 2009b). Ball et al. (2010) estimate the direct cost of air transportation delays as $32.9 billion.

The Bureau of Transportation Statistics (BTS) defines five categories of reasons for airport delays, as shown in Figure 1, weather alone results in a total delay of more than 32% (BTS, 2018). Many researchers did not include weather-related variables in their prediction models; instead, they focused on non-weather related factors such as traffic controls, networking effects and propagation (Ball et al., 2010; Kafle & Zou, 2016; Rebollo & Balakrishnan, 2014; Rupp & Holmes, 2006; Santos & Robin, 2010). The reason that only a few models have focused on weather-related delays (Klein, 2010) is that weather, especially heavy snowfall or thunderstorm is an exogenous shock. This study includes the weather variable in the prediction model because as extreme weather events get more and more frequent due to the climate change the damage is too severe to ignore.



Source: Bureau of Transportation Statistics (2018)

Figure 1 Weather's Share Of Delayed Flight

In order to reduce delays and improve service quality, airports need to invest in infrastructure. Assessing the economic value of the investment in aviation infrastructure has attracted the attention of practitioners and scholars (Zou & Hansen, 2012). Simulation tools that include flight trajectories, weather, route and airport capacity limits, and scheduling to adjust capacity constraints in the system have been used in a number of previous studies. Hansen & Wei (2006) conducted a multivariate post hoc analysis to investigate the impact of large-scale expansion of the Dallas-Fort Worth Airport. In addition, in order to improve on-time performance, they found that delay-reduction benefits were offset by flight demand induction and airline schedule adjustments.

In a series of studies, Morrison and Winston explicitly model passenger demand as either a function of delays (Morrison and Winston, 1983) or the full price of a flight which includes airline operating costs, passenger time costs, landing fees, and delay costs to airlines and passengers (Morrison and Winston, 1989, 2007). Forbes (2008) studies the relation between delays and air flight ticket price. The market structure is also affected by investment because the price response varies with the level of competition. Price responses more extensively when the competition gets more intense, Jorge and de Rus (2004) pointed out that the benefits of airport investment include delayed savings from existing and transfer traffic. In addition, they also believe that the new capacity can increase the starting frequency and the use of smaller aircrafts.

Most studies on snow removal systems have focused on operational efficiency and installation principles (Adl-Zarrabi, Mirzanamadi, & Johnsson, 2016; Lai, Liu, & Ma, 2014; Lund, 2000; Shen et al., 2016). Anand (2015) conducted a benefit and cost analysis of the heated pavement system. However, his calculations were based on the total time of delays by traffic, weather and technical issues, and assumed no changes in demand, supply and price. This study systematically considers the exact impact of snowfall on delays and the investment effects adjusted by the flight market system. We investigated the cost of traditional snow removal systems and heated pavement systems for proper benefit and cost analysis.

CHAPTER 3.0 Heated Pavement System

Flight delays cause an indirect price by adversely affecting airline scheduling and aircraft utilization, and creating additional labor expenses (Britto et al, 2012). Using multi logic model to estimate passenger costs, Morrison and Winston (1989) found that a 1% increase in on-time performance creates a value of $1.21 per round trip per customer. Britto et al‘s research indicates that US consumers would gain about $1.5-2.5 per passenger from a 10% reduction in delays. Total passenger delay cost is estimated up to 16.7 billion dollars. The lost in air transportation demand adds an additional $3.9 billion to the cost side (Britto et al., 2012).

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Winter storms bring runway closures and decrease airport capacities through flight delays and/or cancellations. To avoid dangerous aircraft incidents, most transport category aircrafts are prohibited from operating on runways covered by untreated ice or by more than 1/2 inch of snow or slush. Operators of air transport airports follow specific guidelines for the rapid removal of winter contaminants (snow, slush or ice) from the Aircraft Operations Area (AOA). The airport should have sufficient resources to remove 1 inch of snow from the priority areas of the AOA within a reasonable time. The extent to which these adverse effects of winter contaminants are minimized depends on the strategy implemented by the airport operator.

De-icing/anti-icing on the pavement can eliminate or prevent frost, snow or ice from accumulating on runways, taxiways, aprons, gates and ramps. A combination of mechanical methods and chemical de-icing/anti-icing agents is used for deicing of pavements at airports. Contractors employed by the airport's operating agencies or authorities usually perform runway deicing. Certain ramps, aprons, gates, and taxiway de-icing/anti-icing can be performed by other entities, such as airlines and FBOs operating in these areas. Pavement de-icing usually occurs in the same season as aircraft de-icing, but may be shorter than the aircraft de-icing season.

3.1 Mechanical Methods

Mechanical methods for snow removal, such as plows, brushes, blowers and shovel, are the most common forms of runway deicing and can be combined with chemical methods. The airport usually has multiple snow removal equipment and employees are trained in operations. Since winter storm events may be unpredictable, road de-icing/anti-icing training personnel can be available 24 hours a day at the airport during the winter.

3.2 Chemical Methods

A combination of mechanical methods and chemical de-icing agents is used in most airports to remove ice, sleet and snow. Common road de-icing and anti-icing agents include ethylene glycol, propylene glycol, urea, glycol-based liquids, called UCAR (containing about 50% ethylene glycol, 25% urea and 25% by weight water), potassium acetate , sodium acetate, sodium format and calcium magnesium acetate (CMA). Sand can be used to increase the friction of the icy paved area, but it can be detrimental to the mechanical work of the aircraft.

Salt (i.e. sodium chloride or potassium chloride) can be used in de-icing/anti-icing areas not used in aircraft (e.g. car roads and parking lots), but not for de-icing/anti-icing taxiways, runways, aprons and Ramps because of their corrosive effects. It has been reported that potassium acetate may reduce the insulation properties of electrical systems such as runway lights. An industry working group is currently investigating this issue.

Many airports use mechanical equipment followed by chemical applications to de-ice large amounts of snow and ice. Road surface anti-icing can be performed based on predicted weather conditions and road surface temperatures. Apply de-icing and anti-icing solutions using on-board spray equipment or manual methods. Table 2 shows the unit cost of the deicer.

Table 2 Cost Estimates Of Common Deicers

Deicer	Approximate Cost	Reference	Application Rate
Sodium chloride (NaCl)	\$26/ton	Zang et al (2009)	170-890 lbs/12-ft lane mile (13-68 g/m^2), \$0.0003/m^2
	\$36/ton	Levelton Consultants Limited (2007)	
	\$26-42/ton	Shi et al, (2009b)	

Deicer	Approximate Cost	Reference	Application Rate
	\$66-79/ton	Rubin et al. (2001)	
Magnesium chloride (MgCL2)	\$95/ton	Zang et al (2009) Levelton Consultants Limited (2007)	100-150lbs/12-ft lane mile (8-11 g//m^2) \$0.0002//m^2
Calcium chloride (CaCl2)	\$294/ton	Zang et al (2009)	Used along with NaCl in the U.S., \$0.03/m^2
	\$120/ton	Levelton Consultants Limited (2007)	
	\$267/ton	Rubin et al. (2001)	
Calcium magnesium acetate (CMA)	\$670/ton	Zang et al (2009)	200-500lbs/12-ft lane mile (15-39 g//m^2), \$0.004//m^2
	\$1280/ton	Levelton Consultants Limited (2007)	
Potassium acetate (KAc)		Zang et al. (2009)	0.9 to 9.1 gal/1000 ft^2
Salt mixed with Calcium Chloride (NaCl and CaCl2)	\$98/ton	Zang et al. (2009)	5 to 12 gal CaCl2/ton of NaCl, \$0.01//m^2

Source: Nevada Department of Transportation (2015). P.25

3.3 Alternative Airfield Pavement Deicing/Anti-icing Methods

Heating the road surface to a temperature above the freezing point of the water is an alternative method to prevent icing. In addition to the environmental benefits associated with eliminating emissions of chemicals that are potentially hazardous to the environment, heated pavement systems may also increase passenger safety.

3.3.1 Electrically Heated Pavements.

Current encounters resistance as it flows through the conductor. Current resistance converts electrical energy into heat. The heat generated is proportional to the current flowing through the conductor and the conductor composition that resists the current. Two forms of electrical heating are used for road snowmelt applications. Insulated conductors are embedded in the road surface, such as heating cables or mesh/grid mats. A conductive material is added to the pavement material mixture, electrical energy is applied through the non-insulated conductor, and the pavement is used as a heat source.

3.3.2 Hydronic Pavement Heating

Hydronic refers to the use of heated fluids as a transfer mechanism. Heat is released by thermal conduction. The heated fluid flows through a pipe or pipe embedded in the pavement structure. The cooled fluid is returned to the heat source and the cycle is repeated. The heated liquid can come from a variety of sources. Direct use of geothermal water as a fluid is most effective, but may be limited to areas close to the boundaries of the tectonic plates. Other places need to consider ground source heat pumps, heat exchangers or boilers to increase efficiency and reduce operating costs. If a reliable supply is guaranteed throughout the design life, an alternative heat source, such as waste heat, can be used.

Table 3 Cost of Heated Pavement

	Installation	Operation	Maintenance	Heat source.
Lund (1999)	\$20 / ft^2	\$3,000	\$500	Geothermal system
Minsk (1999)	\$48 ~\$70/ ft^2	\$1.48~\$1.54/ ft^2		Geothermal (bridge)
	\$22~\$26 / ft^2	\$0.98 / ft^2		Electric heating(bridge)
Hoppe (2000)	\$30 / ft^2	\$18/h (gas)	\$1.74/ft^2 ,500/year	Geothermal (bridge)

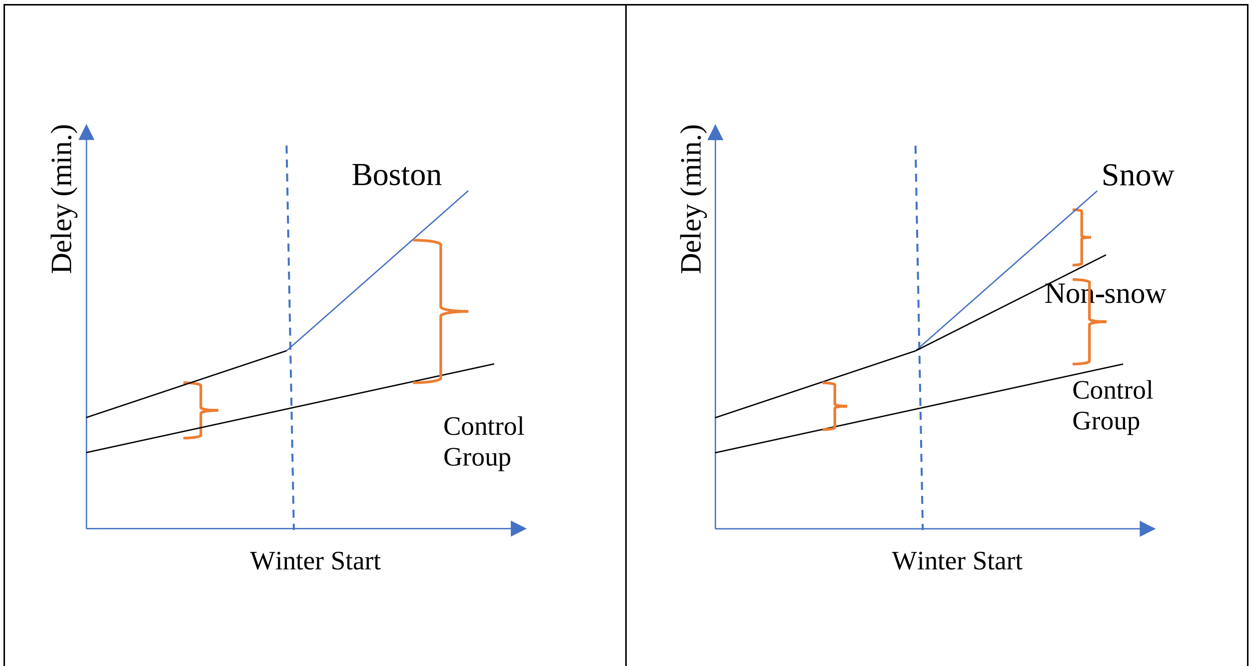
	Installation	Operation	Maintenance	Heat source.
Ziegler et al. (2009)	$325 / ft^2	$31,741 /year		Geothermal
Anand (2015)	$15 ~$65/ft^2	$1.12/ft^2		Natural Gas.

CHAPTER 4.0 Delay Prediction

The goal of the first part of the study is to determine the impact of snowfall on flight delays. Determining the snow effect requires controlling any systemic shocks, such as national and seasonal trends. It is recommended to use several identification strategies to solve the missing data problem caused by the fact that we usually only observe the potential outcome of the treatment. The primary method of identifying snow efficiency is to compare the average difference between snow and non-snow conditions. In this framework of causal reasoning, we use two different methods for more accurate identification. One is structural form regression analysis (parameter mode), and the other is the nearest neighbor that matches one of the non-parametric methods.

4.1 The Difference in Difference Model

The parametric approach we use in this study is the Difference in Difference in Differences method or the so-called Triple Differences (TD). This method is a more advanced method for estimating the treatment effect. The most basic treatment effect analysis is "before-after", which compares treatment outcomes before and after. However, when other variables affect the outcome between time gaps, this difference is not appropriate. The difference (DD) model solves the above problem by combining the before and after analysis with the untreated matched control group. Among the changes of other variables, those caused by the observed variable are explained by controlling the difference in the covariate in the difference model, and those caused by the unobserved variable are negated to some extent by the second layer difference. The basic concept of TD is shown in Figure 2.



Difference in Differences	Triple Differences

Figure 2 Illustration of DD and DDD Identification Approach

The Triple Difference model has an extra difference from the above DD. The difference can be temporal or cross-sectional. Airports located in Boston and Chicago area are in the treatment group. This assumption is reasonable because experience with snow is limited to airports in the northern region, so flights at airports in the southern region can be treated as a control group. Each flight in the northern region in winter has a different snow experience by hour or by day. Therefore, snow-free flight in winter can be another control group in the treatment group.

As shown in Figure 2, the Triple Difference model allows us to control any unobserved effects caused by region-specific shocks. Since we have a dataset with records of snow and non-snow conditions in the same flight group, we can apply triple differences. The Southern Airport

Control Group can capture the trend of air travel at the national level. Just like the simple differences in the difference model, we include time virtualization to eliminate time trends. In our case, we define summer and fall as the pre-snow period and winter as post-treatment period. This regional, seasonal and treatment difference allows us convincingly analyze the snow effect.

$$Delay \quad = \beta_0 + \beta_1 Winter + \beta_2 North + \beta_3 North * Winter$$
$$+ \beta_4 (North \times Winter \times Snow) + \beta_5 X + \beta_6 Airport \quad + \beta_7 Month \quad + u_j$$

β_0*: mean summer delay minutes of control group airports*

β_1: *mean delay difference between control groups summer and winter*

β_2*: Boston and Control groups' summer delay difference.*

β_3*: Boston Areas mean winter delays – Boston Area mean summer delay– (Control group winter delay -Control group summer delay).*

β_4*: Mean delays minutes difference between snow days and non-snow days in Boston winter season*

In this equation, i indexes individual flights, j denotes the airport where flight departs or arrive, and t denotes the month. North indexes airports' location (1 if the northern state, 0 if southern), and winter denotes season (1 if the snow season, 0 is not winter). Delay is the real delay time, X is a vector of observable characteristics: visibility, snow precipitation, temperature, wind speed, flight distance, airport traffic, Airport indicates the origin or destination of flight for control the fixed airport effect, Month is for fixed month effect, and Snow is an indicator for treatment group (1 if snowing, 0 if not snowing).

The coefficient of interest is now β_7 the coefficient of the triple interaction term. The estimate $\widehat{\beta_7}$ can be expressed as follows.

$$Pure\ \widehat{Snow}\ Effect = \beta_4 - \beta_3$$

$$:\left(\overline{Delay}_{North,Snow,Winter} - \overline{Delay}_{North,nonsnow,Winter}\right) - \left(\overline{Delay}_{South,Winter} - \overline{Delay}_{South,Summer}\right) - \left(\overline{Delay}_{North,Winter} - \overline{Delay}_{North,Summer}\right)$$

4.2 Matching analysis

When the treatment group and the control group differed in the observed covariate X, the difference in the result Y could not be attributed to the difference in treatment. In the previous triple difference model, we selected the control group with similar physical conditions, such as airports and regions. However, it may not share similar weather conditions. A better solution is to compare individuals who share the same X value. Choosing such an individual is a "matching," which is a non-parametric way of controlling X.

In this study, we used a rich data set so that we could find the most similar flight from the control group. We build the “matching” in two phases Let $X = (X_1, X_2)$ where X_1 is covariates that should be matched exactly. In the first phase, we match each processed observation to the control group by the departure and destination of the flight. If the treated observations are not paired, we will give up. This process is called stratification. Second, for the treated t in stratum s, matching controls are selected using X_2 only from the same stratum s. We adopt the k nearest neighbor algorithm to match the covariateX_2. We then find nearest observations that had no snow but has the closest value in weather conditions: temperature, visibility, precipitation, wind speed and traffic conditions: departure date and congestion. If K is 1, we call it a pair type matching. However, if K is 4-8, it is a multiple matching (Smith 1997, Busso et al. 2014).

When we both try to find the paired and multiple nearest neighbor observations in stratum s, we use 'Mahalanobis' distance around covariateX_t.

$$(X_t - X_c)' V_N^{-1} (X_t - X_c)$$

Where X_c is indexes the control group and V_n is a sample covariance matrix for X using either T or C group.

We adopted the bias collected multiple matching estimators of Adadie and Imbens (2011).

$$\tau_N^{bc} = \frac{1}{N} \Sigma_{i=1}^{N} \left(\hat{Y}_i^1 - \widehat{Y_i^0}\right)$$

$$\hat{Y}\ _i^1 = D_i Y_i + (1 - D_i) \frac{1}{K} \sum_{t \in T_i} \{\ Y_t + \widehat{\mu_1}(X_i) - \widehat{\mu_1}(X_t)\ \}$$

$$\hat{Y}\ _i^0 = (1 - D_i) Y_i + D_i \frac{1}{K} \sum_{t \in T_i} \{\ Y_c + \widehat{\mu_0}(X_i) - \widehat{\mu_0}(X_c)\ \}$$

Where, $\hat{\mu}_d(X)$ is for $\mu_d(X) = E\left(Y^d \middle| X\right) = E(Y|X, D = d)$. $t \in T_I$ means t belongs to the matched treated for control I, and `$c \in C_i$' means c belonging to the matched controls for treated i. The motivation for this bias collection comes from the fact that when matching is not exact which cause a bias, adding $\widehat{\mu_1}(X_i) - \widehat{\mu_1}(X_t)$ and $\widehat{\mu_0}(X_i) - \widehat{\mu_0}(X_c)$ to avoid this bias. The $\hat{\mu}_d(X)$ is a linear regression estimator in practice.

CHAPTER 5.0 Data

Our data and variables are from two sources. Personal flight information comes from the airline's on-time performance data from the Trans Stats database of the Bureau of Transportation Statistics. Hourly weather information for each airport is from the database at the National Oceanographic and Atmospheric Administration (NOAA) National Environmental Information Center. On-time performance data includes on-time arrival data for major air carriers' uninterrupted domestic flights, departure and arrival delays, origin and destination airports, flight numbers, scheduled and actual departure and arrival times, cancellation or transfer flights, Taxi and taxi time, talk time and uninterrupted distances. We narrowed the data down to the period between April 2014 and March 2015, during which a historic snowfall occurred in the northeast. This feature provides a natural experiment that allows us to test snowfall more clearly.

We chose four airports in the Great Boston area where severe snowstorms happened — Boston Logan International Airport (BOS), T. F. Green Airport (PVD), Manchester - The Boston Regional Airport (MHT) and Worcester Regional Airport (ORH). Information from these airports is used for identifying delay effects. These four airports are located within a 60-mile radius and within one hour drive, hence their intense competition for passengers and airlines. Both airports and airlines need higher capacity and better infrastructure to improve on-time performance of flights and survive the ever-intensifying competition. Under this situation, the case for applying HPS to airports has never been stronger.

We also pick four airports in the Greater Los Ángeles Area where there is no snow — Los Angeles International Airport (LAX), Long Beach Airport (LGB), John Wayne Airport (SNA), Hollywood Burbank Airport (BUR). Similar to the Boston area airports, these airports are also located in close proximity and compete intensely, thus making a great counterpart control group.

Delays vary in different months and airports. We have four different types of delay information, as shown in Figure 3. First, we define the general delay as the time difference between the scheduled and actual departure or arrival times. A negative magnitude of the delay means that the schedule is reached in advance. In addition, we use the taxi-out time - the time between an airplane leaving the gate and the closing of its wheels in departure airports, and the taxi-in time- the time between the opening of wheels and an airplane reaching the gate at the destination airport. We do not use air-born delays because we do not have a scheduled airtime.

Figure 3 Delays at the Airport

Our dataset includes both flight data and weather information. We choose hourly weather information because weather conditions vary across time and daily weather information relates to cancelations rather than delays. We then match a geographically nearest weather observation station to an airport.

Combining flight and weather data sets is a major challenge. The weather observation time is different from the flight departure time, and weather observation does not follow a strict cycle. Ideally, the dataset can be combined according to the closest weather observation time. However, this minimum distance connection is very expensive to perform and not feasible. Instead, we randomly select one weather observation per hour per station and then perform an equivalent connection with the flight departure hour. We lose some data accuracy (for example, there may be 2:54 weather data and an earlier 2:03 flight), but this simplification is critical to making the problem workable. The weather information includes hourly temperature, precipitation of rain and snow, visibility and wind speed. Through this process, we finally have weather conditions in the departure and arrival of each flight. We define the snow variable as there is snowfall during the scheduled departure or arrival time. Snowfall represented hourly snow. We define winter as the period from December to March.

Flight logistics variables are also major factors in delays. In particular, airport congestion is an important determinant of flight delays (Mayer and Sinai 2003a; Mazzeo 2003). To include this factor, we use the daily airport operations initiation (destination), the total number of daily departures and landings at the starting (destination) airport, as a proxy variable for congestion. We also include monthly indicators in all estimates to control demand and seasonal fluctuations. The flight distance is included as another delay determinant.

Figure 4 shows the total operation of each airport during the observation period. LAX is the largest of all. BOS ranked the second. The Southern Airports, LAX, SNA, BUR, and LAS are larger than other northern airports. In addition, the total number of flights arriving at an airport follows the same order. The lower two charts in Figure 4 represent the average number of minutes of delay per airport. It is also different by months and by airports. This graph shows a complex delay mode. The average delay time for large airports such as LAX and BOS is well controlled. It shows also that the average delay increases in winter and summer. Table 4 shows the basic statistics of the data. These descriptive statistics clearly show that the northern airport's delay in winter extends by about 5 minutes. Other delay-related metrics, such as departure, arrival delay, extreme weather delays and taxi-out time, also have longer average delays. These simple statistics give hints that snow has multiple effects on airport operations. It is obvious that flight departure and landing are challenging in the northern area in winter. The below zero temperatures indicate more days with frozen runways and strong winds disrupting flight operations and causing lower visibility in the Boston area.

Table 4 Descriptive Statistics

Variable	Winter		Other	
	North	South	North	South
Delay(minute)	11.378(40.844)	6.176(35.925)	6.104(34.150)	7.371(33.883)
Departure Delay (minute)	12.822(38.957)	9.159(34.308)	8.438(32.795)	9.039(32.703)
Arrival Delay (minute)	10.126(43.323)	4.877(36.710)	3.799(35.680)	5.750(34.652)
Extreme Weather Delay (minute)	3.714(24.178)	1.994(15.196)	2.031(14.430)	1.170(12.279)
Runway Delay : Taxi out	19.761(12.183)	15.740(8.151)	17.462(9.052)	15.471(7.751)
Runway Delay : Taxi in	7.185(5.151)	8.282(6.131)	6.878(4.334)	8.020(5.931)
Snow (1 if snowing)	0.120(0.325)	0(0)	0.007(0.086)	0(0)
Precipitation (inch)	0.002(0.011)	0.001(0.006)	0.003(0.020)	0.000(0.007)
Temperature (F)	29.065(11.595)	63.945(7.639)	59.866(14.446)	69.402(7.520)
Visibility (mile)	8.755(2.789)	8.801(2.321)	9.277(2.104)	9.519(1.359)
Wind Speed (MPH)	11.079(6.000)	5.979(4.407)	10.350(5.125)	7.889(4.858)
Flight Distance (mile)	976.32(741.28)	1034.3(815.65)	1014.5(775.83)	1044.5(824.45)
Flight operates at airports	530.07(242.23)	881.97(421.94)	558.54(242.24)	967.03(455.93)

Variable	Winter		Other	
	North	South	North	South
Observation	60,412	131,475	205,177	426,331

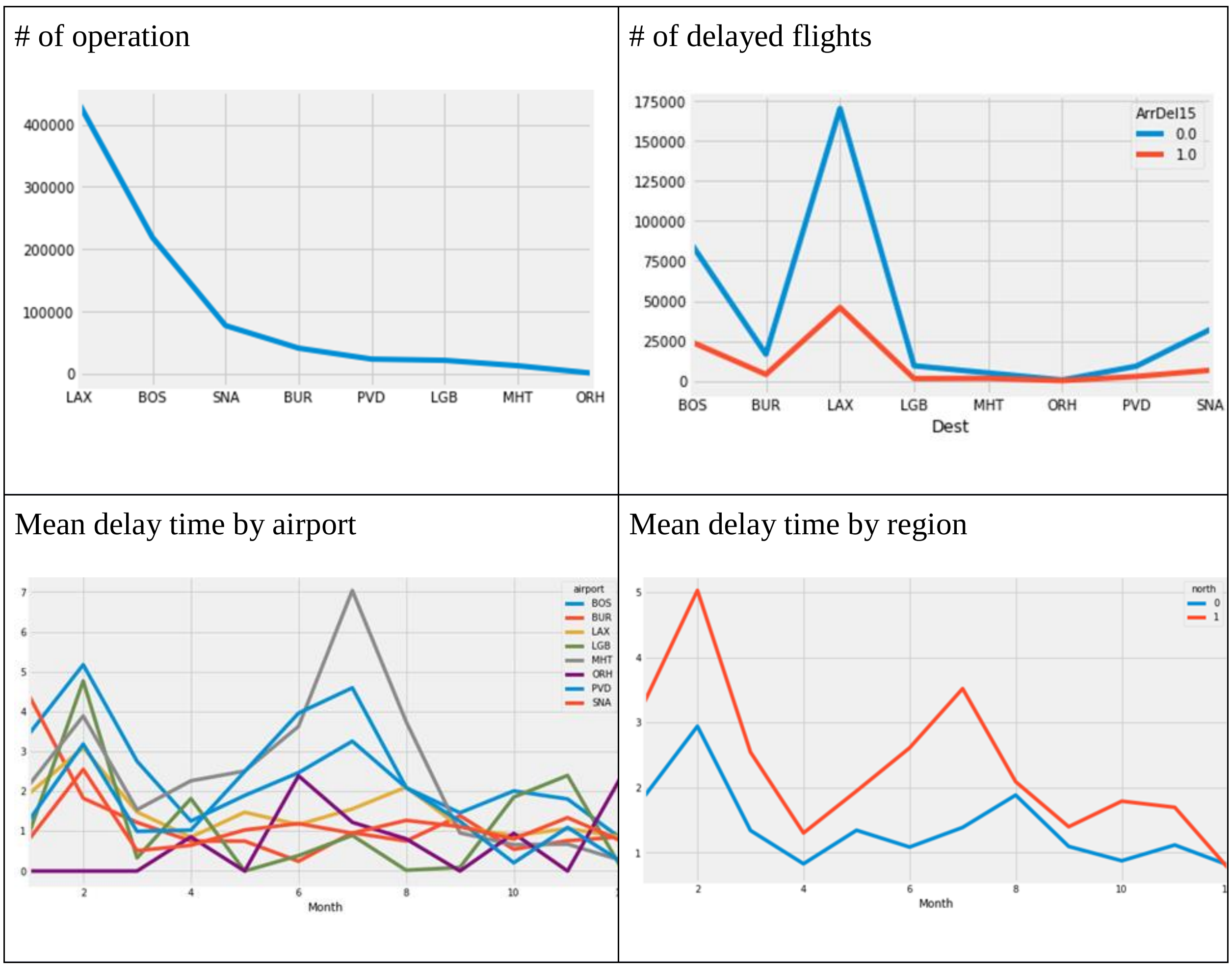


Figure 4 Number of Flights, Number of Delayed Flights and Average Delay

CHAPTER 6.0 Estimation Results

6.1 Triple Difference

Table 2 shows the results of triple different model estimates. All traditional delay measures (overall delays, weather delays, and taxi times) indicate that a snowstorm influenced the flight. Compared with the normal winter, snowfalls extend the delays. Not surprisingly, when the hourly precipitation gets bigger, the situation begins to deteriorate.

Model 1 is the basic treatment effect model to estimate the snow effect. The result indicates snow causes an average 10 minutes of delay. One inch of snow accumulation on a runway causes 169 minutes of delays. If snow on runways is not properly managed, there could be serious traffic congestion at the airport. Model 2 to model 4 show more accurate results of snowfalls. Model 2 shows the impact of snow on general delays. After controlling for the seasonal and regional effects, the specific impact of snowfalls is significantly positive. The result shows if there is snowfall when the flight departs or arrives at the airport, it causes above 5 minutes of delay per flight and that magnitude becomes 3 minutes longer when the flight departs from that airport. Model 3 shows the weather specific delays reported by airlines increase with the snowfall. Snowfalls extend the delay time by about 5 minutes. Model 4 results indicate the time elapsed between the gate and wheel-off or wheel-on significantly affected by snow. It shows both taxi-in and taxi-out time increase by approimately two and a half minutes when snow falls.

Snowfall significantly increases the delay in all models. Warm weather conditions reduce delays. Clear views also reduce latency. However, congestion and flight distance show mixed signals. As the data characteristics show, large airports have more traffic, so they can systematically handle this congestion. In addition, when the flight distance is long, it can compensate for the departure delay by speeding up.

Table 5 Regression Results

	Model 1: Delay		Model2: Delay		Model3: Weather		Model4: Taxi Time	
Variable	coef	std err.	coef	std err.	coef	std err.	coef	std err.
Snow (DDD)			*5.108*	*(0.501)*	*2.478*	*(0.36)*	*2.414*	*(0.101)*
North_Winter			3.432	(0.239)	-0.083	(0.221)	0.504	(0.048)
Snow	9.975	(0.441)	0.292	(0.459)	-0.971	(0.336)	1.409	(0.092)
North	-2.095	(0.379)	-2.782	(0.382)	0.106	(0.365)	-1.019	(0.077)
Winter	-1.337	(0.139)	-2.013	(0.145)	0.602	(0.14)	0.958	(0.029)
Temperature	-0.080	(0.004)	-0.043	(0.005)	-0.006	(0.005)	0.000	(0.001)
Visibility	-0.565	(0.022)	-0.588	(0.022)	-0.202	(0.019)	-0.176	(0.004)
Distance	-0.001	(5E-5)	-0.001	(5E-5)	0.001	(4.7E-5)	0.000	(0.0001)
Congestion	0.014	(0.001)	0.013	(0.001)	-0.005	(0.001)	0.005	(0)
Snow_preci	169.400	(22.247)	165.558	(22.244)	120.217	(11.919)	164.918	(4.466)
Departure	3.123	(0.076)	3.126	(0.076)	-0.721	(0.072)	7.957	(0.015)
Feb	4.789	(0.199)	4.817	(0.199)	1.172	(0.181)	0.355	(0.04)
Mar	2.203	(0.192)	1.972	(0.193)	-0.168	(0.179)	0.531	(0.039)
Apr	-1.403	(0.135)	-1.266	(0.136)	0.194	(0.134)	0.445	(0.027)
May	0.842	(0.139)	0.707	(0.139)	0.843	(0.134)	0.372	(0.028)

	Model 1: Delay		Model2: Delay		Model3: Weather		Model4: Taxi Time	
Variable	coef	std err.	coef	std err.	coef	std err.	coef	std err.
Jun	4.006	(0.146)	3.812	(0.146)	0.904	(0.133)	0.529	(0.029)
Jul	3.839	(0.16)	3.490	(0.162)	1.717	(0.15)	1.000	(0.032)
Aug	1.959	(0.148)	1.630	(0.149)	1.337	(0.142)	0.938	(0.03)
Sep	-1.769	(0.146)	-2.106	(0.147)	0.363	(0.158)	0.428	(0.03)
Oct	-0.804	(0.136)	-0.953	(0.136)	0.205	(0.138)	0.539	(0.027)
Nov	-1.003	(0.134)	-0.821	(0.135)	0.253	(0.134)	0.885	(0.027)
Dec	4.009	(0.134)	4.515	(0.137)	-0.363	(0.116)	1.360	(0.027)
BUR	5.394	(0.495)	4.588	(0.499)	-2.517	(0.484)	-4.131	(0.1)
LAX	-7.969	(0.501)	-8.224	(0.501)	2.219	(0.484)	-3.128	(0.101)
LGB	2.306	(0.535)	1.492	(0.538)	-3.082	(0.538)	-2.835	(0.108)
MHT	8.425	(0.437)	8.276	(0.438)	-2.070	(0.428)	-1.801	(0.088)
ORH	5.286	(0.997)	5.149	(0.997)	-4.614	(0.985)	-2.487	(0.2)
PVD	7.501	(0.374)	7.249	(0.375)	-2.779	(0.366)	-1.929	(0.075)
SNA	3.193	(0.457)	2.385	(0.46)	-2.342	(0.444)	-3.331	(0.092)
intercept	8.339	(0.545)	6.994	(0.55)	6.055	(0.525)	7.455	(0.11)
N	823546		823546		169059		823546	

6.2 Matching Results

For matching analysis, we use the nearest neighbor matching method. To match more effectively, we first precisely match a flight that operates in north and winter then among those subsamples, we select the nearest matching flights. When the algorithm finds a neighbor, the closest one should share similar weather and flight traffic conditions to the flight under consideration, because the dates of the two flights were close to each other. The specification reduces sample size by 823,546 to 191,887 (winter) or 60,412 (winter and arctic conditions), thus reducing bias matching and processing burden. For the second stage of matching, we use weather conditions such as temperature, visibility, precipitation and wind speed. For traffic condition matching, we use the flight distance and congestion of the airport and the operating days of the week.

Table 6 reports the average treatment effect of snow on flight delays. The first column presents the k =1 case and the second column the k=4 case. The average delay impact of winter snowfall on the northern airports is estimated to be 8.1 to 9 minutes. Arrival delay does not significantly change, nor does taxi-in time. Taxi-in time is relatively small, regardless weather type, with some rare exceptions such as airport gridlock. (Allan et al., 2001).

Arrival delay is shorter than departure delay during both the snow season and the entire year. This difference can be explained by airlines' efforts to offset departure delays by shortening airtime and taxing. In addition, the airline includes a buffer time when scheduling the arrival time, so an interruption occurs; the scheduled arrival time will be fine-tuned (Arikan et al., 2013). When we expand the sample to include the southern Airports, the pattern of the snow effect does not change. We used an average treatment effect on the treatment group because there was never snow in the southern airport, so the average snowfall effect at the northern airports was a suitable estimator. When we increased the matched control group to 4, the snow effect showed the robustness of the sign and amplitude of the effect. Departure and taxi time have also increased significantly.

Table 6 Average Treatment Effect: K Nearest Matching Bias Collected Estimator And Standard Error

		K=1	K=4	
	Delay Type	Estimate	Estimate	Number of Sub-sample
ATE	Delay	5.6570***(1.652)	3.7677***(1.155)	60,412: Winter & North
	Departure Delay	9.6242***(2.3309)	8.1250***(1.9918)	30,182
	Arrival Delay	-0.5163 (1.6610)	-0.9811 (1.2457)	30,230
	Taxi Time	3.1735***(0.6696)	3.836***(0.510)	60.412
	Taxi out	5.4574*** (0.0667)	6.2833***(0.5140)	30,182
	Taxi in	0.0696 (0.2085)	-0.0101(0.1717)	30,230
	Weather Delay	-0.3237 (0.9738)	0.0903(0.608)	16,346
ATET	Delay	1.5384(2.3188)	2.7924(1.8073)	191,887 Winter
	Departure Delay	4.8331*(2.4413)	9.1237***(1.8005)	95,926
	Arrival Delay	1.4739 (2.8468)	0.8895 (2.0237)	95,961
	Taxi Time	6.9911***(0.5657)	7.0026***(0.4427)	191,887
	Taxi out	11.5773***(0.6128)	11.6335***(0.4821)	95,926
	Taxi in	0.1256(0.3622)	0.1614(0.2692)	95,961
	Weather Delay	5.5872***(0.5657)	6.0320***(0.7624)	42.656

Note. We use paired and four nearest neighbors. X covariates include visibility, temperature, wind speed, precipitation, congestion, and distance of flight, and matching day of the week.

CHAPTER 7.0 Expected Benefit and Cost of Heated Runway

In this chapter, we calculate the benefits and costs of introducing a heated roadway system to eliminate snow delays at each airport in the Boston area. In order to use the information we obtained from the previous chapter, we use the Net Present Value method (NPV). The net present value is an indicator of the increase in social value of investment, and has the following formula in our case.

$$NPV = \sum_{t=0}^{20} \frac{R_t}{(1+i)^t} - Construction\ Cost$$

R_t: $Benefit_t - OperatingCost\ Differnce_t$

i: $discount\ factor$

t: time

We assume that each airport introduces the heated runway individually. The initial construction cost of each airport will depend on the size of its runway. The second assumption regards the period for this investment. We assume that optimal runway replacement cycle is 20 years and during which market conditions remain. Air traffic is expected to change every year. Therefore, as the US Federal Aviation Administration recommends, we adopt an annual growth rate of 2.8% over the next 20 years. The discount rate discounts future cash flows as the present value. We adopt the effective interest rate of the United Nations (2.15%) reported to the World Bank.

First, we define the benefit of the heated runway as saved cost of snow delays as reduced by the new system. We take into consideration only the direct cost to the airlines of a snow delay.

$$\text{Benefit}_{\text{airline}} = \alpha * \text{Average snow delay time} * \text{Air craft operation} * \text{Carrier Delay Cost}$$

where α is the reduction rate. $Average\ snow\ delay\ time$ is what we estimated previously. We assume 9.62 minutes of additional delays happens whenever there is snow. $Aircraft\ operation$ is the number of arrived and departure flights that delayed by snow effect. In 2015, BOS had 7,549, MHT had 389, and PVD had 768 flights that operated under snowy weather as shown in Table 7. Carrier delay cost is the average cost of aircraft block time for U.S. passenger airline. According to Airline for America, one minute of delay in 2015 results in $62.55 of additional operation and maintenance costs such as crew, pilot salary, and extra fuel consumption, etc.

Table 7 Operations of Airports Located in Boston Area in 2015

	Operation under Snow	Total Operation	% of Snow Affected Cases	Average Passenger per Flight
BOS	7,549	218,605	3.5%	89.7
MHT	289	13,078	2.2%	42.2
PVD	768	23,718	3.2%	54.8

Second, to calculate the overall benefit of passengers in each airport, we survey the average passenger per flight and time value for the customer who uses the flight. In 2015, Boston airport' average passenger per flight was 89.7, and 42.2 for MHT, and 54.8 per PVD respectively. According to Federal Aviation Administration (2016), individual passenger's value of travel time per hour was $47.10

Table 8 shows the calculated benefit for each airport's investment. Assuming that the Heated Pavement System is installed on all runways and all snow-related delay is eliminated, we get the benefit of this system by adding benefits from airline and passengers. In the case of Boston Logan International Airport, an expected benefit is $4,542,467 for airlines and

$5,113,598 for passengers. This benefit can be achieved when the HPS operates perfectly and is well maintained.

Table 8 Expected Benefits Of Installing Heated Runway at Boston Airports

			Total Benefit
BOS	$4,542,467	$5,113,598	$ 9,656,065
MHT	$173,900	$92,099	$ 265,999
PVD	$462,129	$317,824	$ 779,953

In order to calculate the net benefit of the new HPS, it is necessary to study its installation costs, operating costs and maintenance costs. In this NPV analysis, we are concerned about whether the initial cost can be recovered from the HPS revenue. We assume that operating costs are very low and the long initial construction time and costs are the major concern. The installation costs of the system are different from different airports. The unit cost per square foot is $15 to $45.

Table 9 Estimated Cost Of Installing Heated Runway at Boston Airports

		Cost of Construction	
	Runway Area (ft^2)	$15 per ft^2	$45 per ft^2
BOS	7,861 x 150	$ 17,687,250	$ 53,061,750
	10,006 x 150	$ 22,513,500	$ 67,540,500
	7,001 x 150	$ 15,752,250	$ 47,256,750
	5,000 x 100	$ 7,500,000	$ 22,500,000
	2,557 x 100	$ 3,835,500	$ 11,506,500
	10,083 x 150	$ 22,686,750	$ 68,060,250

		Cost of Construction	
	Runway Area (ft^2)	\$15 per ft^2	\$45 per ft^2
	Total	\$ 89,975,250	\$ 269,925,750
MHT	9,250 x 150	\$ 20,812,500	\$ 62,437,500
	7,650 x 150	\$ 17,212,500	\$ 51,637,500
	Total	\$ 38,025,000	\$ 114,075,000
PVD	8,700 x 150	\$ 19,575,000	\$ 58,725,000
	6,081 x 150	\$ 13,682,250	\$ 41,046,750
	Total	\$ 33,257,250	\$ 99,771,750

Table 10 shows the NPV of the heated runway pavement installment over a 20-year analysis period. Only the low-cost case for Boston Logan Airport produces positive net present value around USD11million, indicating that the project is economically feasible. Other airports with limited traffics, such as MHT and PVD, cannot justify the high initial construction costs by producing enough benefit for each airline and passenger.

Table 10 Net Present Value of Installing Heated Runway at Boston Airports

	Scenario	Benefit of Airline	Total Benefit
BOS	Low cost	\$4,549,149	\$110,958,239
	High cost	-\$175,401,350	-\$68,992,260
MHT	Low cost	-\$34,406,307	-\$32,489,815
	High cost	-\$110,456,307	-\$108,539,815
PVD	Low cost	-\$23,640,787	-\$17,027,173
	High cost	-\$90,155,287	-\$83,541,673

Note: NPV over 20 year and discounted at 2.15%

Reference

Adl-Zarrabi, B., Mirzanamadi, R., & Johnsson, J. (2016). Hydronic Pavement Heating for Sustainable Ice-free Roads. *Transportation Research Procedia*, *14*, 704–713. https://doi.org/10.1016/j.trpro.2016.05.336

Airlines For America. (2016). U.S. Passenger Carrier Delay Costs. Retrieved March 5, 2018, from http://airlines.org/dataset/per-minute-cost-of-delays-to-u-s-airlines/

Pritha Anand, Ali Nahvi, Halil Ceylan, Vasiliki Dimitra Pyrialakou, Konstantina Gkritza, Kasthurirangan Gopalakrishnan, Sunghwan Kim, and Peter C. Taylor (2017). Energy and Financial Viability of Hydronic Heated Pavement Systems. FAA

Allan, S. S., Beesley, J. A., Evans, J. E., & Gaddy, S. G. (2001). Analysis of delay causality at Newark International Airport. In *4th USA/Europe Air Traffic Management R&D Seminar* (pp. 1–11).

Arikan, M., Deshpande, V., & Sohoni, M. (2013). Building Reliable Air-Travel Infrastructure Using Empirical Data and Stochastic Models of Airline Networks. *Operations Research*, *61*(1), 45–64. https://doi.org/10.1287/opre.1120.1146

Ball, M., Barnhart, C., Dresner, M., Hansen, M., Neels, K., Odoni, A., … Zou, B. (2010). Total delay impact study. *NEXTOR Research Symposium*, *Washington DC. Http://Www. Nextor. Org*.

Britto, R., Dresner, M., & Voltes, A. (2012). The impact of flight delays on passenger demand and societal welfare. *Transportation Research Part E: Logistics and Transportation Review*, *48*(2), 460–469. https://doi.org/10.1016/j.tre.2011.10.009

Bureau of Transportation Statistics. (2018). Understanding the Reporting of Causes of Flight Delays and Cancellations. Retrieved March 6, 2018, from https://www.bts.gov/topics/airlines-and-airports/understanding-reporting-causes-flight-delays-and-cancellations

Cook, A. J., & Tanner, G. (2011). European Airline Delay Cost Reference Values. *Eurocontrol*.

Cook, A. J., Tanner, G., & Anderson, S. (2004). Evaluating the True Cost to Airlines of One Minute of Airborne or Ground Delay. Final report. Brussels, Belgium Eurocontrol.

Derwin, D., P. Booth, P. Zaleski, W. Marsey and W. Flood Jr (2003). "SNOWFREE® heated pavement system to eliminate icy runways." Management 2012: 03-16

Farha, M., Y. Hassan, A. A. El Halim, A. Razaqpur, A. El-Desouky and A. Mostafa (2002). Effects of new deicing alternatives on airfield asphalt concrete pavements. Federal Aviation Administration Technology Transfer Conference.

Hansen, M., & Wei, W. (2006). Multivariate analysis of the impacts of NAS investments: A case study of a capacity expansion at Dallas-Fort Worth Airport. *Journal of Air Transport Management*, *12*(5), 227–235. https://doi.org/10.1016/j.jairtraman.2006.05.002

Hoppe, E. J. (2000). Evaluation of Virginia's First Heated Bridge, *Journal of the Transportation Research Board.* 1741(1), 199-206.

Kafle, N., & Zou, B. (2016). Modeling flight delay propagation: A new analytical-econometric approach. *Transportation Research Part B: Methodological*, *93*(Part A), 520–542. https://doi.org/10.1016/j.trb.2016.08.012

Klein, A. (2010). Airport delay prediction using weather-impacted traffic index (WITI) model. In *29th Digital Avionics Systems Conference* (p. 2.B.1-1-2.B.1-13). https://doi.org/10.1109/DASC.2010.5655493

Lai, Y., Liu, Y., & Ma, D. (2014). Automatically melting snow on airport cement concrete pavement with carbon fiber grille. *Cold Regions Science and Technology*, *103*, 57–62. https://doi.org/10.1016/j.coldregions.2014.03.008

Levelton Consultants Limited (2007). Guidelines for the selection of snow and ice control materials to mitigate environmental impacts, Transportation Research Board.

Lund, J. W. (2000). Zinc Meters Snow. Geo-Heat Center Quarterly Bulletin, Vol. 21 No. 2 (Complete Bulletin). A Quarterly Progress and Development Report on the Direct Utilization of Geothermal Resources. *Geo-Heat Center Quarterly Bulletin, 21*(2).

Lund, J. (2000). "Pavement Snow Melting." GHC BULLETIN, JUNE 2000 http://geoheat.oit.edu/bulletin/bull21-2/art4.pdf((Retrieved on April 3, 2014)). Lund, J. (2014). "Pavement Snow Melting. ." Geo-Heat Center, Oregon Institute of Technology, Klamath Falls, OR. http://goite.org/documents/PavementSnowMelting.PDF(Retrieved on February 18, 2014).

Rebollo, J. J., & Balakrishnan, H. (2014). Characterization and prediction of air traffic delays. *Transportation Research Part C: Emerging Technologies*, *44*(Supplement C), 231–241. https://doi.org/10.1016/j.trc.2014.04.007

Rubin, J., P. Garder, C. Morris, K. Nichols, J. Peckenham, P. McKee, A. Stern and T. Johnson (2010). "Maine Winter Roads: Salt, Safety, Environment and Cost." A report by the Margaret Chase Smith Policy Center, The University of Maine.

Rupp, N. G., & Holmes, G. M. (2006). An Investigation into the Determinants of Flight Cancellations. *Economica*, *73*(292), 749–783.

Santos, G., & Robin, M. (2010). Determinants of delays at European airports. *Transportation Research Part B: Methodological*, *44*(3), 392–403. https://doi.org/10.1016/j.trb.2009.10.007

Shen, W., Ceylan, H., Gopalakrishnan, K., Kim, S., Taylor, P. C., & Rehmann, C. R. (2016). Life cycle assessment of heated apron pavement system operations. *Transportation Research Part D: Transport and Environment*, *48*, 316–331. https://doi.org/10.1016/j.trd.2016.08.006

Zou, B., & Hansen, M. (2012). Flight Delays, Capacity Investment and Social Welfare under Air Transport Supply-Demand Equilibrium. *Transportation Research Part A: Policy and Practice*, *46*(6), 965–980. https://doi.org/10.1016/j.tra.2012.02.015

Zhang, J., D. Das and R. Peterson (2009). "Selection of effective and efficient snow removal and ice control technologies for cold-region bridges*." Journal of Civil, Environmental, and Architectural Engineering* 3(1): 1-14.